Online Measurement of Molten Phases

Technical Field

The present invention is directed to identifying and quantifying information from molten phases, including slags, fluxes, metal, and matte. Using a method based upon principal components analysis of image data taken from the surface of molten phases.

Background Art

Multivariate image processing provides a reliable method for extracting information from image data. This method has been successfully applied for image processing in several applications, such as satellite image data and the medical area. However, there is no prior application of this method for online measurements of molten phases.

Availability of a reliable real time measurement of a process is an important factor for developing any control system. In the case of high temperature molten phases processing such as steel making, due to the extreme conditions, it is difficult and costly to carry out real time measurements. Currently, several methods for gathering information of molten phases, such as detection of the relative surface areas of molten phases and assessment of whether the phases are fully molten, rely on visual observations by human operators. Therefore, there is a clear need for more reliable online measurement of molten phases.

An object of this invention is to delineate and quantify online information about molten phases within a reasonable computation time for detecting the relative surface areas of molten phases, determining whether the phases are fully molten, and predicting the temperature of the phases. Since the computation time is significantly fast, the method can be used as an online measurement device and integrated into a control system.

Disclosure of the Invention

In accordance with the invention, there is provided a method of characterizing molten phases using principal components analysis of image data taken from the surface of molten phases. The method developed involves (a) developing a standard and (b) using the standard to identify and quantify an online image data. For purpose of standard development, the procedure developed consists of the following steps: (i) taking a digital image of the surface of molten phases, (ii) performing principal component analysis of the image, and (iii) judging the standard values of the principal components, based on the knowledge of the molten phases properties, which will be used to determine the properties of online images. In using a standard to identify and quantify an online image data, the following steps are carried out: (a) taking a digital image of the surface of molten phases, (b) performing principal component analysis on the image, (c) comparing this analysis with standard values of the principal components to determine the properties of the images, and (d) quantifying the considered properties of the image.

Description of Drawings

Figure 1 depicts a schematic diagram of the online measurement of molten phases. Basically, the system consists of three main parts, i.e. molten phases being measured, a digital camera for taking image data, and a computer for processing the image data;

Figure 2 shows an example of an RGB image taken from molten phases;

Figure 3 shows a schematics diagram of the principal component analysis procedure;

Figure 4 depicts an example of the first two principal components plot (t_1 versus t_2) from the image in Figure 2;

Figure 5 is a plot correlating of predicted bare metal area, presented together with inert gas flowrate injected from the bottom of vessel, as a function of gas injection time; and

Figure 6 is a plot correlating the temperature of the bath and the average second principal component, $\mathbf{t}_2$, for slag properties.

Best Mode for Carrying Out the Invention

A schematic depiction of an online measurement system of molten phases is generally indicated by reference numeral 20 in Figure 1. As shown in the figure, this system 20 is applied to measuring molten phases in a vessel 22 and includes a digital camera 24 for taking image data, and a computer 26 for processing the image data.

The very first step for measuring the properties of molten phases, such as disruption of a slag surface, partial solidification of a slag phase, or

temperature of the slag, is capturing image data of the slag surface using the digital camera 24 in RGB (Red-Green-Blue) format. The RGB format is a common way to represent high-resolution colour images, which each pixel is specified by three values—one each for the red, green, and blue (RGB) components of the pixel's colour. In a colour image of Figure 2, the white areas of the image correspond to bare metal, yellow areas correspond to thin slag, brown areas correspond to fluid slag, and black areas correspond to solidified slag. Such an image may be schematically represented as a stack of three congruent n x m pixel images. Mathematically, the image can be viewed as a matrix, I_m, with dimension n x m x 3, as shown in Figure 3. Such an image taken from the surface of a steel making ladle is visually represented in Figure 2. Digital image data are transmitted into the process computer 26 to determine the properties of the molten phases based on the information captured by the image data.

In processing the captured image data of molten phases, principal component analysis or PCA is used. PCA is a multivariate statistical procedure applied to a set of variables, which are highly correlated, with the purpose of revealing its principal components (or score vectors). The principal components are linear combinations of the original variables, which are independent of each other and that capture most of the information in the original variables into its first few principal components [Jackson, 1991].

Multivariate statistical methods, e.g. principal component analysis (PCA) and partial least squares (PLS), have been successfully used for multivariate image analysis [Esbensen et al., 1989; Geladi et al., 1989; Grahn et al., 1989; Bharati and MacGegor, 1998]. Using these approaches, a set of highly dimensioned and highly correlated data can be projected into a set of un-correlated data with a reduction in dimensionality. In this invention the PCA approach is used to evaluate the image of molten phases.

For simplifying the problem, the three-way matrix $I_{m(mxnx3)}$ of Figure 3 is unfolded into an extended two-way matrix $X_{((n.m)x3)}$, as illustrated in Figure 3.

$$\underset{(n \times m \times 3)}{I_m} \xrightarrow{unfold} \underset{(mn \times 3)}{X} \qquad (1)$$

The unfolded image matrix, **X**, is decomposed by performing principal component analysis [Jackson, 1991]. The relation between the original matrix and its principal component is given by the following equation:

$$X = \sum_i t_i p_i^T + E = TP^T + E \qquad (2)$$

where: **X** is an unfolded version of $\mathbf{I_m}$; **T** is a score matrix; **P** is a loading matrix; and **E** is a residual matrix.

By assuming that all information in the image is retained in the first two principal components, i.e. $\mathbf{t}_1$ and $\mathbf{t}_2$, then $\mathbf{X}$ matrix can be approximated by:

$$\hat{X} = \sum_{i=1}^{2} t_i p_i^T \tag{3}$$

The score vectors, $\mathbf{t}_i$, are linear combinations of the variables (columns) in the data matrix $\mathbf{X}$ that explain the greatest variation in the multivariate data. These vectors have a property of orthogonality with respect to each other. Loading vectors, $\mathbf{p}_i$, are the eigenvectors—in descending order—of the variance-covariance structure ($\mathbf{X}^T\mathbf{X}$) in the data matrix. These vectors have a property of orthonormality with respect to each other (i.e. $\mathbf{P}^T\mathbf{P} = \mathbf{I}$; where $\mathbf{I}$ is the identity matrix). Based on the property of the score and loading vectors, the value of score matrix, $\mathbf{T}$, can be obtained by multiplying $\mathbf{X}$ by $\mathbf{P}$ [Geladi et al., 1989]:

$$\mathrm{T=XP} \tag{4}$$

Following the assumption that all information in the image is retained in the first two principal components, the combination of the first two score vectors (t_1 and t_2) would be almost identical with these pixels [Bharati and MacGregor, 1998], as shown mathematically in equation (3). Therefore, the combination of these principal components can be used to extract information from (or to discriminate materials in) the considered image. In addition, the average of the pixel intensities at each wavelength is

represented by t_1, whilst the contrast or difference among the pixel intensities at various wavelengths is represented by t_2 [Bharati and MacGregor, 1998]. In accordance with the invention, the average value of t_1 or t_2 may be used to characterize the property of an image, such as to determine the temperature.

The image data from the image presented in Figure 2 was unfolded by using the procedure given in Figure 3 to give matrix **X**. Analyzing the principal component of matrix **X** using a standard procedure of PCA [e.g. Jackson, 1991] gives values of loading vector, $\mathbf{p}_i$, and eigenvalues presented in Table 1. All computation for this report is performed in a high-level computer language, i.e. MATLAB™ Version 6 and MATLAB™ Image Processing Toolbox Version 3.

Table 1. Loading vectors and eigenvalues of the image presented in Figure 3.

SCORE	1	2	3
Loading vector	0.7002	-0.5738	-0.4247
	0.6189	0.1915	0.7617
	0.3558	0.7963	-0.4893
Eigenvalue	0.2458	0.0387	0.0081
Total variance, %	84	13.23	2.77

As shown in Table 1, the cumulative of total variance of the first two principal components is 97.23% (84.00% and 13.23 %, respectively). Therefore, it is reasonable to assume that the majority of information in

the considered imaged is retained in the first two principal components; the combination of these principal components can be used to extract information from (or to discriminate materials in) the image and then, only the first two principal components are used in the subsequent analyses. The loading vectors for these two principal components are

$$p_1^T = [0.70020.61890.3558] \text{ and } p_2^T = [-0.57380.19150.7963].$$

A scatter plot of the first two score vectors ($\mathbf{t}_1$ versus $\mathbf{t}_2$) is presented in Figure 4. The figure has 3110400 score combinations plotted, one for each of the **2160 x 1440** pixel locations in the original image. It is interesting to note that there were several overlaps of points in the figure due to the large number of pixels to be plotted into the graph and similar features in the original image yielded similar score vector combination.

By projecting the values of the first two principal components ($\mathbf{t}_1$ and $\mathbf{t}_2$) of the pixels to the corresponding image, the information in the original image that is explained by the combination values of $\mathbf{t}_1$ and $\mathbf{t}_2$ can be identified. The results from this process can be used to delineate the pixel class. Using the combination values of $\mathbf{t}_1$ and $\mathbf{t}_2$, and combined with information representing an area by one pixel, the area of an object under consideration in the image can be determined. The results from this process can be used to delineate the pixel class that is given in Table 2. By using this approach, if the represented area of one-pixel is known, then the total area under consideration can be determined by multiplying the area of one-pixel with the number of points at a same

group in Figure 4. For example, using this approach to calculate the area of a spout eye or bare metal area observed in the steel making ladle of in Figure 2 gives a value of 1.764 m^2.

Table 2. Mapping of the first two principal components to information in original image.

t_1	t_2	Original Image
1.1475 to 1.2634	0.2995 to 0.5322	Eye (white)
0.6138 to 1.1475	-0.2245 to 0.2995	Thin slag (yellow)
0.0790 to 0.6138	-0.3356 to –0.1998	Fluid slag and ladle wall (brown)

Figure 5 shows an example of predicted bare metal area, presented together with inert gas flowrate as a function of gas injection time. As clearly shown in the figure, the area of bare metal is a function of inert gas flowrate. Clearly from the preceding discussion, the method according to the invention can be used to delineate the surface properties, such as disruption of slag or bare metal and partial solidification of slags and to quantify the surface attributes in term of its area.

Since the second principal component, t_2, represents the contrast or difference among the pixel intensities at various wavelengths [Bharati and MacGregor, 1998], the average value of the second principal component is used to quantify the temperature of the bath. The relationship between temperature and intensity will also be a function of the reflecting properties of the material, which in part is a function of ladle chemistry.

Figure 6 shows a correlation between temperature of the bath and the

average second principal component, $\mathbf{t}_2$, for various slag grades. As shown in Figure 6, there is a good indication that the temperature of the bath can be represented by the average value of the second principal component, $\mathbf{t}_2$. Hence, it can be concluded that the temperature of molten phases, including slags, fluxes, metal, and matte can be determined using the average value of $\mathbf{t}_2$.

In order to apply the image processing results as a real time measurement data, it is important to be able to process the image in a reasonable period of time. In the present work, the processing time for measuring the bare metal area is a few seconds. Therefore, it can be concluded that the computation speed is adequate for an online measurement system. The calculations were performed on an IBM™ compatible Pentium III/800 MHz personal computer with 250 MHz RAM running in a Windows™ 2000 environment and using MATLAB™ Version 6 and MATLAB™ Image Processing Toolbox Version 3.